Face Images Dimension Reduction using Wavelets and Decimation Algorithm

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Abstract— *This paper demonstrates a novel lower dimension multi resolution analysis technique to represent facial images using wavelet transform and decimation, which alleviate heavy computational load, reduce noise, produce a representation in low frequency domain and hence make the facial images less sensitive to facial expressions and small occlusions. All coefficients of wavelet transform do not have information needed for face classification. This work also selects the most appropriate wavelet coefficients required for recognition. In preprocessing phase to reduce computational load, Automatic Cropping Algorithm (ACA) is applied for scale normalization which removes unnecessary details except face from image and at the same time facial tilt has been addressed through reverse rotation process. Image decimation is carried out to compute the recognition results at different image resolutions and to compensate varying facial expression. The experiments have been performed on ORL and FERET datasets with different resolutions; success rate up to 99% on ORL dataset is achieved.*

Keywords— Image processing, biometrics, face recognition, image decimation and wavelets.

1. Introduction

Unlike human beings who have the excellent capability to recognize different faces, machines are still lacking this aptitude due to variation in image illuminations, complex backgrounds, visual angles and facial expressions. Therefore face recognition has become a complex and challenging task. Research on this issue as a part of computer vision is nearly 20 years old [1]. The subject has become a major issue, mainly due to the important real-world applications of face recognition like smart surveillance, secure access, telecommunication, digital libraries and medicine. The details of these applications are referred to in the surveys [2,3,4,5]. Face recognition techniques have been divided into feature-based approach [6,7,8] the appearance-based approach [9,10 ,11 ,12] and the hybrid approach [13].

Wavelet transform techniques are not too old and these techniques are being used in modern signal and image processing including multiresolution analysis, sound synthesis, computer vision, graphics and image compression [14]. Wavelet transform techniques achieve optimal decomposition without affecting much the image quality. At the same time wavelet transform and wavelet packet analysis have provided a new subspace for image recognition. Fotlyniewiez [15] proposed an automatic face recognition using nonlinear filtering to enhance intrinsic features of face and a high order neural network classifier was used for training and recognition of faces. Lee and Chung [16] employed the wavelet-based Fisher Linear Discriminant (FLD) recognition process. Zhu and Orchad [17] captured local discriminative features in the space frequency domain for face detection using wavelet packet analysis. Ma and Tang [18] used discrete wavelet face graph matching approach for the purpose. Liu [19] used Haar wavelet for effective human face detection. [20] is an application of nonlinear wavelet approximation to recognize faces and the advantages of nonlinear wavelet approximation are compared with its linear counterpart.

The paper comprises of three parts. In the first part, image preprocessing is carried out where color images are converted to gray scale, image scale normalization is carried out using ACA and image tilt compensation technique is applied. In second part Discrete Wavelet Transform (DWT) is applied on decimated images to ascertain the image resolution against best recognition results. In the last part experiments on ORL and FERET datasets are discussed.

2. Preprocessing

2.1 Color Image to Gray Scale Conversion

Color images being in three planes of Hue, Saturation and Value are computationally very extensive. To avoid color images handling they are converted to gray scale images by using expression:-

$$Y = 0.3R + 0.59G + 0.11B \qquad (1)$$

The weights are used to compute gray image because for equal amount of color eye is most sensitive to green, red and then blue [21, 22].

2.2 Automatic Cropping Algorithm (ACA)

Canny edge detection mask with suitable threshold value is applied on image with uniform back ground to extract the outer curvature of the face as shown in figure 1.

Figure 1 Result of Canny Operator

Binary image obtained in result of edge detection is scanned from left to right, top to bottom in a classic pattern and four points shown in Figure 2 are worked out. The image scale normalization (ISN) using the values of equation 4 is carried out as shown in Figure 3.

$$ISN = value\left(C_{\max} - C_{\min}\right), value\left(R_{\max} - R_{\min}\right) \qquad (2)$$

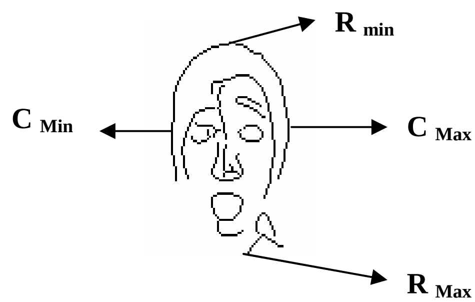


Figure2. Four outer points of face curvature

Where C_{Max}, $C_{Min,}$ R_{Max} and R_{min} are maximum and minimum values of column and row respectively.

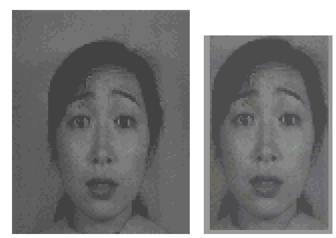


Figure 3. Original Image and Result of ACA

2.3 Facial Tilt Compensation

Eyes in face image are pivot point for tilt compensation. Pixels values near eyes change more rapidly as compared to rest of face image. This property of image is used to detect the general eye location in the face image. Iris localization in the rough region of eye is carried out through template matching and center points *(xl,yl)* and *(xr,yr)* of left and right eye are determined. These are then used to compute the tilt (slope, *m*, and angle, θ) in the image using:

$$m = (yr - yl) / (xr - xl) \quad (3)$$

$$\theta = \arctan(m) \quad (4)$$

Finally, the tilt compensation is applied using the reverse rotation, i.e., rotating by $-\theta$ example is shown in Figure 4.

Figure 4: Image with and without Tilt

3. Image Decimation

Decimation algorithm [23] scans through lines of pixels or group of pixels according to decimation down scale factor (M). As a result Gaussian Pyramid of varying image resolution is obtained. Decimation process is shown in Figure 5.

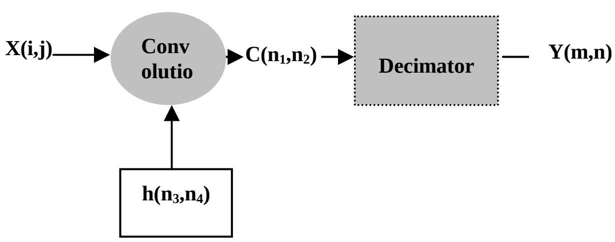


Figure 5. Image Decimation Process

Here X(i,j) is input image, $h(n_3,n_4)$ is convolution averaging mask and $C(n_1,n_2)$ is convolved image without zero padding. Y(m,n) is the out put decimated image.

$$Y(m,n)=C[\,n_1M,n_2M] \qquad (5)$$

Where M is decimation down scale factor and

$$0 \le m \le (n_1/M),\ 0 \le n \le (n_2/M)$$

The resulting image is a reduced size mirror of the original image faithful in tonality to the original but smaller in size.

4. Wavelet Application For Multiresolution Analysis and Dimension Reduction

The DWT has been used for texture classification [24] and image compression [25] due to multiresolution decomposition property. The wavelet decomposition technique was also used to extract the intrinsic features for face recognition [26]. In wavelets packet analysis both the high and low frequency filters are iterated but in wavelet transform, only the low pass filter is iterated where it is assumed that only low frequencies contents contribute more than the higher frequencies to represent information in face images. This assumption is most valid for face images where the interest lies in the low frequency components.

Let a discrete signal I(x,y) be characterized by a trend signal (low frequency signals) and a fluctuating or detailed signal (high frequency signals). In wavelet multiresolution approximation [27] a unique scaling factor $\phi(x)$ with compact support exist such that if we denote

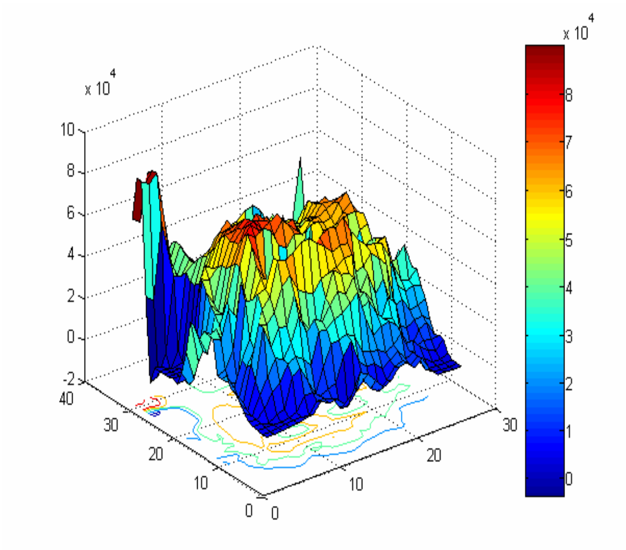
$$\phi_{2^j}(x) = 2^j \phi\left(2^j x\right) \mathit{for}\ j \in z\ \mathit{the\ family\ of\ function}:$$

$$\left(\sqrt{2^j}\,\phi_{2^j}\left(x - 2^{-j} n\right)\right)_{n \in z}$$

is an orthonormal basis in $L^2(R)$. A discrete approximation of signal I(x) at resolution 2^j can be represented by

$$A_{2^j}^{d} I(x) = \left(< I(u), \phi_{2^j}\left(x - 2^{-j} n\right) >\right) n \in z \quad (6)$$

Which is equivalent to lowpass filtering followed by uniform sampling at the rate of 2^j. In this proposed model Symlets has been applied on preprocessed, decimated face images for face recognition. Symmetrical, orthogonal and biorthogonal properties of symlets wavelet are exploited to obtain the low frequency image components which provide best image recognition. As not all the coefficients of a wavelet transform have the information needed for classification, a threshold value for each dataset is defined below which coefficients do not contribute much towards recognition. All such coefficients are made zero which helps in reducing overall computational burden. Plot in Figure 6 reflects the effect of threshold on wavelet coefficients. One of the major advantages of wavelet transform is its lower computational complexity as Fast Fourier transformation (FFT) has computational complexity of $O\left(n.\log_2(n)\right)$ whereas in case of wavelet transform it goes down to $O(n)$.



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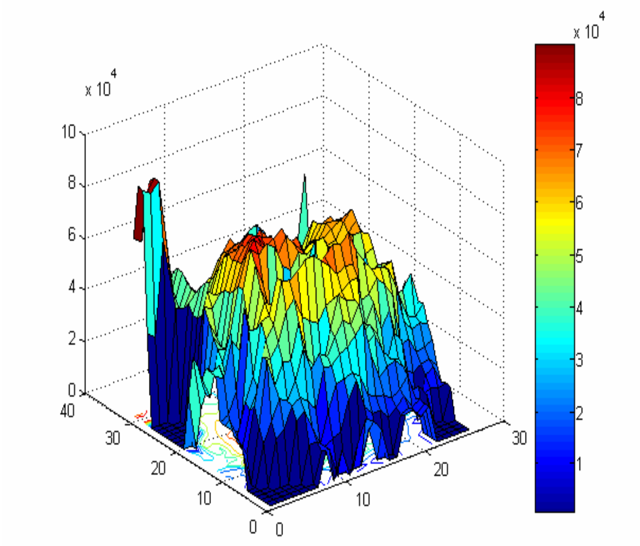

Figure 6. Wavelet Coefficients before applying threshold (Upper); after applying threshold (Lower)

5. Experiments

The trend (low frequency) coefficients of face images reduce the noise and minimize varying facial expressions. These low frequency coefficients of five images of each class are retained as feature vector for classification. Rests of images of dataset are randomly used as test images. For matching and classification purpose in feature space, a natural choice is Euclidian distance metric:

$$d_e\left(\vec{x},\vec{y}\right) = = \sqrt{\sum_i \left(x_i - y_j\right)^2} \qquad (7)$$

While varying the decimation factor, experiments on ORL and FERET datasets were carried out and it was established that each database at a specific resolution provides best recognition results. Results reflect that at decimation factor two ORL dataset provides success rate up to 99% as shown in Figure 9.

5.1 Olivetti Research Laboratory Face Database

The presented recognition system is evaluated on the Olivetti Research Laboratory face database. This database contains 10 different images for each of 40 people. The images of the same person are taken at different times, under slightly varying lighting conditions and different facial expressions. Some people are captured with and without glasses. The head of the people in the images is slightly tilted or rotated.

Figure 7. Examples of ORL data set images

5.2 Feret Database

The second database we have used is FERET database which is established by Army research laboratory USA. We have taken 10 images of 100 persons with total of 1000 images for our experiment. Few examples of these images are shown in Figure 8 and results with varying resolution are shown in Figure 9.

Figure 8. Examples FERET data set images

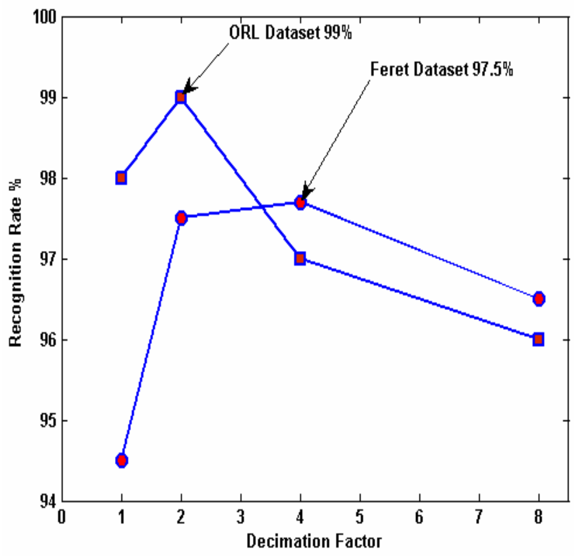

Figure 9. Results of ORL and FERET Dataset Images with Varying Resolution Factor

6. Discussions and Conclusion

In preprocessing phase, color images are converted to gray scale images, tilt compensation is applied and to enhance the computational speed of the system automatic scale normalization is carried out. Symlet4 DWT (level one) was applied on decimated images to obtain recognition results with varying resolution level. Results reflect that images with more high frequency components are more sensitive to resolution variations as compared to face images with lesser high frequency components. Moreover image decimation and DWT decomposition have minimized the facial expression variations and facial changes up to a certain level. This technique is not only computationally less extensive as compared to other wavelet recognition techniques but also provides best recognition results of 99% on images with various constraints like with or without glasses, sad, happy, sleepy, surprise, wink, open / closed eyes, smiling and non smiling faces.

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